Review of European Studies; Vol. 16, No. 2; 2024
ISSN 1918-7173 E-ISSN 1918-7181
Published by Canadian Center of Science and Education

Assessing the Dynamic Productivity of Ghana's Fishery Industry

Christabel Sakpata Ewedji[1], Stephen Afenyo Dehlor[2]

[1] Department of Transport, Faculty of Maritime Studies, Regional Maritime University, Accra, Ghana

[2] Academic Registry, Regional Maritime University, Accra, Ghana

Correspondence: Stephen Afenyo Dehlor, Academic Registry, Regional Maritime University, Accra, Ghana

Received: May 22, 2024 Accepted: July 31, 2024 Online Published: October 31, 2024

doi:10.5539/res.v16n2p29 URL: https://doi.org/10.5539/res.v16n2p29

Abstract

This paper is to statistically and empirically evaluate the dynamic productivity of fishery firms in Ghana, explore the drivers of this productivity change and investigate the contextual variables that impact dynamic productivity. A quantitative research methodology that includes extensive structural equation modeling to explore causal relationships and determine the relative strengths of various variables was used. This paper through a two-stage non-parametric DEA Malmquist analysis investigates the dynamic productivity of fishery firms using 20 registered Ghanaian fishing vessels from 2008 to 2021. In the first stage, the bootstrapped dynamic productivity of the fishery firms are ascertained. The second stage explores the impact of some external factors on the first stage estimations through advanced robust econometric techniques. The result of the first stage showed that the firms' dynamic productivity regressed by about 1%, and this was mainly driven by technological change. The Malmquist Productivity Change was further decomposed into 4 factors, and it was revealed that there exist statistical differences in the drivers of the MPI. The results of the random effect robust regression from the second stage revealed that all variables (AGE, EXC, FIN, LOA, INF, GDP and Covid) are statistically significant, with EXC exhibiting a negative relationship. Again, although LOA is positive, it showed no influence on the MPI.

Keywords: bootstrapping, data envelopment analysis, dynamic productivity, malmquist productivity index

1. Introduction

Over the past few decades, fisheries and aquaculture has steadily taken over globally as a sector generating quite a substantial quantity of animal food (FAO, 2009). The world's oceans globally yield an average of about 67 million tons of fish (World Bank, 2012). Over 200 million peoples' livelihoods directly depend on fish catch from the inland and aquaculture sectors, as this sector provides over one billion people with essential sustenance (about 50% of the animal protein needed by about 400 million people in developing countries).

Ghana's marine subsector accounts for over 70% of domestic production (World Bank, 2012). In the global economy, fish products are widely traded and eaten, with a bigger flow from developing to industrialized countries. Fish is increasingly being consumed locally in Ghana, making it the most popular, and least priced animal protein (Sarpong et al., 2005). According to Asiedu et al. (2017), the yearly per capita consumption of fish is estimated at 26kg, which is higher than the 20 kg global average. This accounts for about 60% of animal protein intake by Ghanaians. Marine capture fisheries, inland fisheries, and aquaculture make up Ghana's fisheries sector (MoFAD, 2018). In addition to providing essential animal protein, Akpalu, Eriksen, & Vondolia (2018) found that, the fisheries sector employs 20% of the labor force, and this includes women who work solely in the processing and distribution chain. Fishing-related foreign exchange earnings overall grew by 9.3% in volume between 2010 and 2015, resulting in an increase in foreign exchange revenues of US$165.7 million in 2010 to US$309.7 million in 2015 (Doku et al., 2018). The estimated contribution of Ghana's fishery sector to GDP is 1.2 percent, while the mother industry, agriculture, contributed 6.6 percent to GDP (OCEAN, 2015). The aforementioned figures confirmed the industry's immeasurable contributions to national economic development as well as citizens' livelihoods. Several studies have examined the sector's productivity growth due to its significance to academics, researchers, and managers (Andersen et al., 2008; Asche et al., 2007; Guttormsen, 2002; Tveteras, 2002).

Some investigations utilized parametric methodology to focus on particular aspects, some of which include agglomeration (Tveteras, 2002; Tveteras & Battese, 2006), production risk (Kumbhakar & Tveteras, 2003), inefficiency (Asche et al., 2009) and learning (Nilsen, 2010). Even though there have been several studies conducted in the field of fisheries, some of these studies have limitations. DEA Malmquist Productivity Indices was used by (Wang et al., 2021b) to assess the effectiveness of 17 fishing firms. The study examined the efficiency of the 17 Vietnamese fishing companies using both constant return to scale (CRS) and variable return to scale (VRS). However, it did not extend its analysis to include a second stage bootstrapping procedure. These constraints clearly highlight the necessity for further research in this area. Also, In order to re-evaluate productivity change on Polish farms, Latruffe et al. (2008) did not perform a second stage bootstrapping analysis, yet they employed bootstrapped Malmquist indices.

Data Envelopment Analysis, a non-parametric methodology have been extensively adopted in various sectors. Some of the sectors include: banking (Asmild et al., 2004; Stewart et al., 2016), insurance (Cummins et al., 2010; Grmanová & Strunz, 2017), agriculture (Mao & Koo, 1997; Toma et al., 2015), oil and gas (Bansal, 2019; Borodin & Mityushina, 2020) and fishery (Liu et al., 2021; Vázquez-Rowe & Tyedmers, 2013). DEA is known for its several advantages, however, it has demerits and one of which is that, DEA does not measure the overall productivity index, particularly, where frontiers change over time is considered. Also, where data is sparsely populated (unbalanced panel), DEA is not helpful.

Some of the fishery productivity researches were conducted by (Weninger, 2001; Asche et al., 2013b; Pan et al., 2020; Deveci et al., 2020; Li et al., 2020). Several studies have examined the dynamic productivity of fishery sector; however, they are limited in Ghana. Out of the many drawbacks identified in literature, the following are worthy to note. Firstly, there is scanty use of bootstrap in fishery efficiency and productivity studies. Secondly, there are few application of double bootstrapping and robust econometric methods. This research is a novel one that adopts double bootstrapping to handle statistical noises/extremes of DEA methodology in the marine fishery sector of Ghana. Thirdly, there are limited fishery efficiency and productivity studies in Ghana. Finally, the study investigates the impact of exogenous factors on the estimated dynamic productivity as well as a comparative performance of Ghanaian vessels. This paper aims to statistically and empirically evaluate the dynamic productivity change of fishery firms in Ghana, explore the drivers of this productivity change and investigate the contextual variables that impact the dynamic productivity through identification of the inputs and outputs variables of fishery firms in efficiency and productivity change studies, assessment and decomposition of the productivity change of fishery firms in Ghana and investigating the impact of exogenous factors on the estimated productivity change.

2. Methodology

There is a widespread interest among individuals, groups, and organizations to assess performance over a particular period and identify areas where they can adjust improve efficiency. This allows individuals and management of organizations to effectively manage and conserve resources. The growing attention on performance has led to the advancement in academic research specifically centered on performance management practices. The study of DEA has rapidly advanced during the period, with many studies directly related to the pioneering work of Charnes et al. (1978) who developed methods to ascertain the efficiency of decision-making units. DEA is a deterministic non-parametric, mathematical programming approach that quantifies the relative efficiency and productivity changes of a group of Decision-Making Units (DMUs) with multiple inputs and outputs that are not necessarily in proportion. It operates under the assumption of free disposability and provides a single measure of efficiency while determining optimal input and output levels for evaluated organizations.

A quantitative approach is embraced which includes the collection of data in numerical format that can be subjected to rigorous quantitative analysis in a formal and organized manner. Unlike other methods, DEA does not require a pre-defined production function, as it is derived from the data through programming techniques (Färe et al., 1989). The primary goal is to identify the most efficient producer, whether it is an existing producer from the data or a combination of multiple efficient producers (Mizala et al., 2002). To establish the efficient frontier, the inefficiency of a Decision-Making Unit (DMU) is evaluated based on its distance from the enveloping hull, which signifies the potential for efficiency improvement. On one hand, the frontier demonstrates the maximum achievable outputs using various input combinations. On the other hand, it represents the minimum input requirements for diverse outputs. DMUs located below the frontier are considered inefficient, while those on the frontier are deemed efficient (Constantin et al., 2009). DEA relies on extreme observations, making it sensitive to outliers (Cooper et al., 2007; Scippacercola & D'Ambra, 2013). While DEA offers advantages by requiring fewer assumptions, it assumes the absence of random errors and considers any deviation from the efficient frontier as inefficiency. However, there are limitations to using DEA. Firstly, it attributes inefficiency to factors that most firms have no control over. Additionally, random errors may be present in the available data. However, since DEA does not account for random errors, a few extreme observations can lead to exaggerated estimations of production possibilities for a given set of inputs. To mitigate this, the research incorporates bootstrapping, a technique that helps remove random noise from the dataset.

DEA primarily concentrates on frontier analysis rather than central tendencies. Unlike statistical regressions, which involve fitting a regression plane through the center of the dataset, DEA focuses on determining the efficient frontier using a piecewise linear surface that “floats” on top of the observations. This perspective allows DEA to uncover relationships that might remain hidden from other methodologies. For example, determining what is meant by "efficiency" or comparing the efficiency of different DMUs can be straightforwardly accomplished by DEA without explicitly formulating assumptions or variations required in linear and nonlinear regression models. The Malmquist index has seen increased popularity in recent years as a metric for assessing productivity change. In order to compute the Malmquist index, 4 different DEA linear programming problems which includes two own periods efficiency estimates and two mixed periods efficiency estimates. The Malmquist index estimation requires efficiency in the current period $\Phi^t(x^t, y^t)$, efficiency in the next time period $\Phi^{t+1}(x^{t+1}, y^{t+1})$, efficiency of a firm in the next period relative to the frontier of firms in this time period $\Phi^t(x^{t+1}, y^{t+1})$ and finally the efficiency of firms in this time period relative to the frontier of firms in the next time period $\Phi_c^{t+1}(x^t, y^t)$. To formalize the MPI, define $\Phi^t(x^t, y^t)$ and $\Phi^{t+1}(x^{t+1}, y^{t+1})$, as the own period output distance functions for a firm in period t and t+1 respectively and $\Phi_c^{t+1}(x^t, y^t)$.and $\Phi^t(x^{t+1}, y^{t+1})$ as the cross period output distance functions, CCD defined the MPI of the firm in period t under CRS as:

$$MPIo(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{\Phi_c^t(x^t, y^t)}{\Phi_c^t(x^{t+1}, y^{t+1})} * \frac{\Phi_c^{t+1}(x^t, y^t)}{\Phi_c^{t+1}(x^{t+1}, y^{t+1})} \quad (1)$$

Färe, Grosskopf, Lindgren, and Roos (1992), constructed and empirically tested the input-oriented MPI as the geometric mean of the two CCD-type indices in the context of non-parametric linear programming DEA. They did this by combining the ideas from Farrell (1957) and Caves et al., (1982) on efficiency and productivity measurements respectively. However, some researchers were of the view that, not all firms operate under CRS and this was how studies investigated the MPI's four-part decomposition (Simar & Wilson, 1998; Wheelock & Wilson, 1999; Zofio & Lovell, 1998). The 4 factor decomposition is attributed to the seminal work of Wheelock & Wilson (1999).

3. Discussion

3.1 First Stage

Two inputs are used to produce two output, and estimates to productivity change of fishery firms in Ghana under VRS from 2008 to 2021 in order to assess how Ghanaian fishery firms judiciously utilizing their resources for economic efficiency given the resources.

Table 1. Summary Statistics of first stage variables (Pooled, 2008-2021)

		Labour (Number of Crew onboard (In '000s)	**Operating cost (in USD$)**	**Carton of fish (in '000)**	**Profit (in USD$)**
		X1	**X2**	**Y1**	**Y2**
Pooled	Count(N)	280	280	280	280
	Mean	32.95	33827.22	18976.14	514475
	SD	11.16	23694.04	5445.9	479139.5
	Min	13	3871.1	6890.5	6078
	Max	67	81982.9	34679.7	2897891
	Time F-Statistic	0.278	1935***	16.11***	269.1***

This observation is supported by the higher standard deviation values, which are compared to the mean values of both the input and output variables. The higher standard deviations indicate greater dispersion or variability in the data, further reinforcing the notion of differences in the sizes of the countries being examined. The mean values of the inputs show that, on average 32.95 crew are employed onboard the vessels while average operational cost accounted for 1,514,716 million of USD. Considering the outputs, carton of fish is represented by 18976.14 in '000s while the profit obtained represents an average 514,475 US dollars.

3.1.1 Productivity Change Assessments From 2008 to 2021

The bootstrapped Malmquist Productivity Index of fishery firms in Ghana are ascertained and further decompose into Pure Technical Change, Pure Efficiency Change, Scale Technical Change and Scale Efficiency Change in order to identify the key driver(s) of the change. This is crucial for understanding the performance of Ghanaian registered industrial fishing vessels over time and adopting effective policies to improve them.

Table 2. Bootstrapped Productivity change 2008/2009

DMU	c11	c22	c12	c21	v11	v22	v12	v21	MPIv
MENG XIN 6	1	0.796	1.078	0.858	1	0.817	NA	0.879	0.796**
MENG XIN 5	1	0.552	1.327	0.582	1	0.966	NA	1.147	0.492**
AP 703	0.539	0.621	0.555	0.6	0.931	0.902	0.9	1.006	1.116**
LU RONG YUANGYU 222	0.488	0.552	0.626	0.57	0.902	0.902	0.915	1.046	1.015**
MARINE 707	0.499	0.636	0.652	0.557	0.905	0.909	0.91	0.92	1.044**
MARINE 711	0.574	0.543	0.762	0.577	0.911	0.982	0.915	1.168	0.846**
RICO SIETE	0.49	0.533	0.508	0.56	0.835	1	0.729	1.196	1.095**
SEA PLUS 87	0.516	0.586	0.547	0.592	0.959	0.895	0.891	1.006	1.108**
SEA PLUS 89	0.508	0.646	0.549	0.752	1	1	0.927	1.253	1.32**
AFRICA STAR	0.957	0.905	0.961	0.997	1	0.941	0.961	1.203	0.991
AGNES 1	0.687	1	0.742	1.102	1	1	1.014	1.281	1.47**
ATLANTIC PRINCESS	1	0.92	1.139	1.017	1	0.95	NA	1.079	0.906
ATLANTIC QUEEN	1	0.922	1.06	0.989	1	0.965	NA	1.224	0.927**
IRIS-J	0.782	1	0.834	1.181	0.972	1	0.948	1.239	1.345**
LONG TAI 1	0.929	1	1.009	1.099	0.998	1	1.009	1.111	1.083**
LONG TAI 2	1	0.949	1.111	0.964	1	0.955	NA	1.163	0.907**
PANOFI DISCOVERER	0.705	0.754	0.616	0.826	0.755	0.825	0.625	1.014	1.198**
PANOFI FORERUNNER	1	0.678	1.136	0.729	1	0.974	NA	1.109	0.66**
PANOFI MASTER	0.635	0.829	0.573	0.897	0.746	0.829	0.609	1.008	1.43**
PANOFI PATHFINDER	1	1	1.02	1.047	1	1	1.082	1.244	1.013

c11=own period efficiency score under CRS, c22=own period efficiency score under CRS, c12= cross period efficiency score under CRS, c21=cross period efficiency score under CRS, v11= own period efficiency score under VRS, v22= own period efficiency score under VRS, v12= cross period efficiency score under VRS, v21= cross period efficiency score under VRS, MPIv=Malmquist Productivity Index under VRS, ciM.1= lower bound confidence interval at 5% **α**, ciM.2= upper bound confidence interval at 5% **α**

The bootstrapped productivity score for 2008/2009 is 1.00, and this means that, on average, all the firms are productive. Geometric means are employed in calculating DEA efficiency estimates due to the nature of these estimates as ratios, which can be skewed. Overall, although the average productivity of the firms shows stagnation, relatively 50% of the firms in the industry experienced productivity growth. The fishery industry's productivity could experience substantial enhancement with growth, as the number of firms progressing far surpasses those encountering decline. There were a striking number of firms whose dynamic productivity was quite low, as evidenced by the longer and thinner lower tail of the distributions especially before 2009.

3.1.2 Average Productivity

The table below displays the yearly averages of the estimated productivity indices, denoted as "MPI". Geometric means are utilized for these calculations, considering that DEA efficiency estimates are in the form of ratios and may exhibit skewness. Additionally, the 95 percent confidence intervals provided offer insight into the statistical significance of the productivity indices.

Table 3. Average Productivity

		95% Confidence Interval	
Period	MPI	LB	UB
2008_2009	1.0381	0.96705	1.0999
2009_2010	1.284493	1.250843	1.339893
2010_2011	0.9151	0.88705	0.9662
2011_2012	1.10835	1.0472	1.20315
2012_2013	1.1065	1.06435	1.19805
2013_2014	0.98065	0.9524	1.0203
2014_2015	0.78025	0.7449	0.8053
2015_2016	0.6445	0.5905	0.6735
2016_2017	1.0274	0.96135	1.09595
2017_2018	1.0576	0.94135	1.1155
2018_2019	0.92135	0.84675	0.9793
2019_2020	1.03035	0.98195	1.125
2020_2021	1.084543	1.065421	1.128263
Geometric Average	**0.985364**	**0.932238**	**1.04288**

*p < .10. **p< .05. ***p<.01.

growth or decline is significant if confidence interval does not include 1

It can be inferred that the periods between 2008 and 2021 saw rather fluctuating productivity changes. The period between 2010-2011, 2013-2014, 2014-2015, 2015-2016 and 2018-2019 recorded worse performance in the industry. Interestingly, the industry did not experience a consistent productivity growth. Results from Table 3 above shows that the productivity of fishery firms regressed by an average of 1.5% (.i.e. [0.985–1]×100) during the sample period. This is primarily caused by periods of productivity regress in 2010-2011 (8.5% decline) and marginal decline in 2013-2014 (2%), 2014-2015 (22%), 2015-2016 (35.5%) and 2018-2019 (7.9%). Despite this, conducting statistical inferences through bootstrapping reveals that the average decline of 1.5% is not significant. Therefore, it is more probable that the productivity has stagnated, as indicated by the confidence intervals encompassing the value one (Simar & Wilson, 1999; Tortosa-Ausina et al., 2008). The year 2009-2010 saw the most significant growth in the industry with about 28%; this is followed by a 10.83% growth in 2011-2012, and 10.65% in 2012-2013. The period 2009-2010 recorded a significant progress of 28%, and this was the paramount progress that the industry has seen within the entire study period. Also, 2011/2012 and 2012/2013 also recorded 11% progress.

The fluctuations in the overall productivity of Ghana's fishery industry can be attributed to trends within the industry. During the global slowdown triggered by the recession in the US due to the credit crunch of 2008, the global economy witnessed a sluggish recovery until around 2011 or 2012 when countries began to regain stability. However, between 2008 and 2010, the industry experienced notable productivity growth, possibly attributable to the high price environment prevailing during that period. The results shows that the average dynamic productivity for Ghana fishery firms from 2008 to 2021 is 0.985. This shows that Ghana fishery firms have regressed by an average of 1.5 and need to improve their performance over time in order to be productive.

3.1.3 Trends in Productivity Change (2008-2021)

Trends in productivity change are the patterns observed over time in the efficiency levels of a given system or industry. Productivity is a measure of how efficiently resources are utilized to produce goods and services, and changes in productivity can have significant implications for economic growth, competitiveness, and overall well-being. Some factors that can influence trends are technological advancements, education and training and resource optimization.

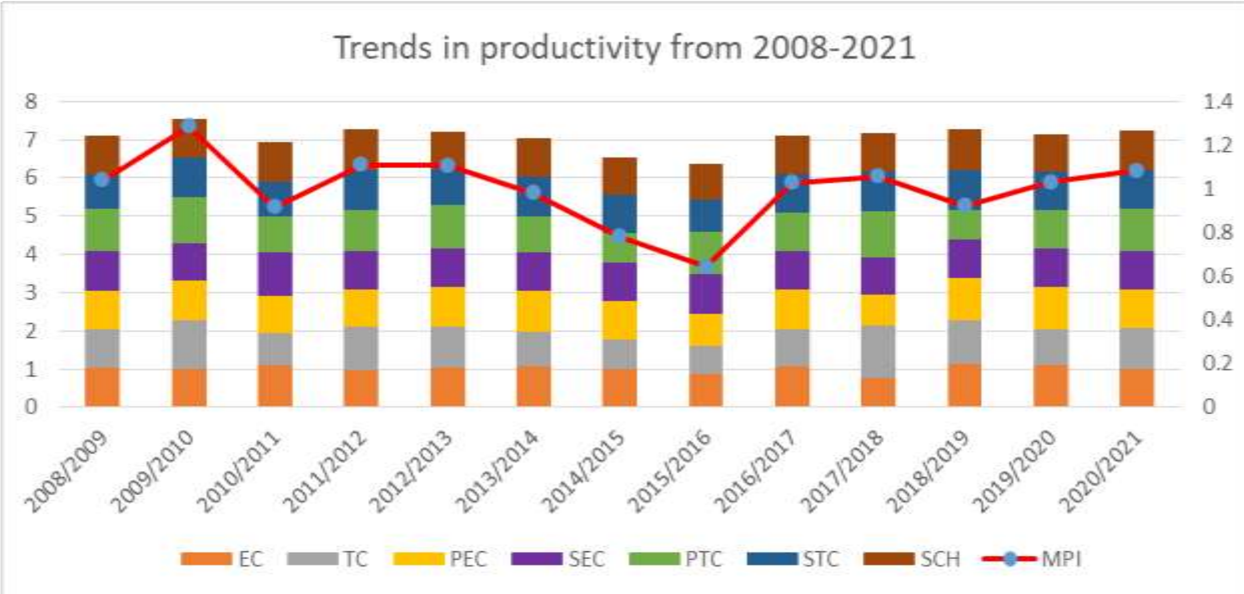

Figure 1. Trends in productivity Change (2008-2021)

The trends in productivity change between 2008 and 2021 are based on the provided averages of the indices for various productivity measures in figure 1 above. Malmquist Productivity Index (MPI) has a value below 1 (0.998) and this suggests a slight decrease in overall productivity over the given period. Efficiency Change (EC) increased slightly (1.005) and this indicates an improvement in overall efficiency during the period. While Technical Change (TC) and Pure Efficiency Change (PEC) increased slightly, (1.015) and (1.003) respectively, TC suggests advancements in technology and methodologies, contributing positively to productivity while PEC indicates a marginal improvement in pure efficiency. Scale Efficiency Change (SEC) and Pure Technological Change (PTC) increased, thus (1.009) and (1.036) respectively, SEC suggests an enhancement in scale efficiency, possibly indicating improved resource utilization at a larger scale while PTC suggests notable improvements in pure technological aspects, reflecting advancements in technology independent of scale.

While Scale Technological Change had a value below 1 (0.98) which indicates a decrease in scale-related technological change, Scale Change (SC) had a score greater than 1 (1.011), which suggests a change in scale, indicating potential shifts in the overall size or scope of operations.

The trends in productivity change between 2008 and 2021 are characterized by a nuanced combination of factors. While there is evidence of improvements in efficiency, technological change, and overall scale, the slight decrease in the Malmquist Productivity Index suggests that these positive aspects are counteracted by certain challenges, possibly related to scale-related technological change. A comprehensive analysis is needed to understand the intricate dynamics influencing productivity trends and to formulate strategies for sustained and balanced productivity growth.

3.2 Second Stage Regression (Fishery Productivity Change and Exogenous Factors)

The first stage involves the estimation of the MPIv and its components whereas the second stage is when the estimated indices are regressed on some environmental covariates in order to establish the influence of those regressors on the regressand. This two-stage analysis is well documented in the DEA and stochastic frontier analysis literature (R. Banker et al., 2019; Daraio & Simar, 2007; Hoff, 2007; McDonald, 2009; Ramalho et al., 2010; Léopold Simar & Wilson, 2011, 2015).

3.2.1 Descriptive Statistics of Second Stage Variables

Based on the dynamic productivity and fishery efficiency literature, the following variables were selected as the determinants of productivity change in Ghanaian Fishery Firms: age of the vessel (AGE), exchange rate (EXC), financial crises (FIN), length overall of the ship (LOA), inflation (INF), Gross Domestic Product (GDP), and Covid-19. Table 4 below presents the descriptive statistics of the variables used in the various second stage analysis.

Table 4. Descriptive statistics of second stage variables

	MPIv	AGE	EXC	FIN	LOA	INF	GDP	Covid
Count	260	260	260	260	260	260	260	260
Mean	1	23.35	1.24	0.23	57.32	2.46	1.62	0.22
SD	0.27	16.52	0.66	0.42	9.96	0.3	0.66	0.41
Min	0.45	0	0.34	0	39.96	1.97	0.1	0
Max	2.06	47	2.3	1	72.5	2.96	2.64	1

Note: AGE=age, EXC= exchange rate, FIN= financial crises, LOA= length overall of the ship, INF= inflation, GDP=Gross Domestic Product, and Covid=Covid-19

The mean values of the second stage variables show that, MPI which represents the independent variable has a mean of 1, age has a mean of 23.35, exchange rate denoted by EXC has a mean of 1.24, financial crises denoted by FIN has a mean of 0.23, Length overall denoted by LOA has a mean of 57.32, inflation denoted by INF has a mean of 2.46, GDP has a mean of 1.62 and Covid has a mean of 0.22.

3.2.2 Regression Analysis

Multiple examinations were carried out to assess the suitability and robustness of various regression models, including Pooled OLS, Fixed Effect (FE), Random Effect (RE), as well as two instrumental variable regressions, 2SLS and Systems GMM. The results from the Pooled OLS analysis reveal that four out of seven variables exhibit statistical significance, boasting p-values of 0, and VIFs below 10 (with the highest being 3.67). These findings indicate that the Pooled OLS regression results are robust, and no further investigation is necessary to enhance their reliability. A Durbin-Wu-Hausman (DWH) test was executed to determine the appropriate panel regression model, whether it be Fixed Effects (FE) or Random Effects (RE). The obtained p-value from the DWH test, which exceeded 0.05, led to the failure to reject the null hypothesis. As a result, it was concluded that no correlation existed between the ui and the explanatory variables, implying the suitability of the Random Effects model. Consequently, the potential presence of serial correlation using the Breusch-Godfrey (1981) was tested. The results indicate that, at a significance level of 0.1%, the null hypothesis (H_0) is rejected, concluding that the dataset indeed exhibited serial correlation.

Table 5. Total Sample regression results

	POLS	Fixed Effect	Random Effect	RE-HAC	RE-PCSE	RE-SCC	**2SLS**
(Intercept)	1.824026***						
AGE	0.001262	0.0053943	0.0018557.	0.001856	0.001856*	0.001856*	-0.001005
EXC	-0.22058***		-0.0709198.	-0.07092	-0.07092*	-0.07092*	-0.852897***
FIN	0.116923**	0.1706988	0.0772663.	0.077266	0.077266.	0.077266.	1.013912***
LOA	-0.00022	-0.0064321	0.0027535.	0.002754	0.002754*	0.002754*	-0.002931
INF	-0.24242**		0.2160007***	0.216001**	0.216001***	0.216001***	0.604935***
GDP	-0.03139	0.1132302	0.1641919***	0.164192***	0.164192***	0.164192***	0.178439.
COVID	0.236206***		0.3035375***	0.303538.	0.303538***	0.303538***	1.659037***

Source: Author's Construct

To address issues related to heteroscedasticity and serial correlations, Beck & Katz (1995) introduced the panel corrected standard errors (PCSE) estimator. The results, along with robust standard errors for the selected random effect, are presented under the "RE Beck & Katz-SCC" column. Model 1 to 7 showed corroborate outcome. In three of the regression models, AGE, LOA and GDP were not statistically significant although AGE demonstrated a positive relationship, LOA and GDP were negatively correlated. Furthermore, EXC, FIN, INF and Covid were statistically significant, however, EXC and INF exhibited a negative relationship with MPI. In the Coeftest, AGE became significant at 0.05 level, leaving LOA and GDP still insignificant.

Table 6. Total Sample regression results continuation

Diagnostic Tests	POLS	Fixed Effect	Random Effect	2SLS	GMM
R^2	0.15652	0.022346	0.053061	0.885	
F statistics	6.68031***	1.27427***	3682.26***		
Breusch-Godfrey test for serial correlation (RE)			23.358		
Breusch-Pagan LM test for, cross sectional dependence (RE)			510.11***		
Pesaran CD test for cross sectional dependence (RE)			15.255***		
DWH for endogeneity (2SLS)				379.6***	
J Hansen Test (over-identifying restrictions)					2693.7
Wald test (Chisq)				379.6***	77.391***
Number of observations	260	260	260	260	
Number of instruments					

The regression is random effect robust which applies Newey-West standard errors on the random effect results. The outcome shows that all variables are now significant, as it is a great tool to correct heteroscedasticity and autocorrelation.

4. Conclusion

The findings have raised some important concerns worthy of consideration in Ghana's fishery sector and dynamic productivity assessments literature. First, the vast and significant differences observed in all variables across time gives clear evidence that size matters in Ghana's fishery sector. Further, the selected firms in the sector were found to be operating under the VRS production technology. This implies that the firms are not operating at optimal scales, thus, the existence of either increasing returns, decreasing returns, or both in the industry. According to Ohene-Asare et al., (2019), firms operating under increasing or decreasing returns to scale are also experiencing economies or diseconomies of scales respectively. In this context, such firms have the potential to improve by either increasing or decreasing their scales of operations to achieve optimal levels in the long.

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Acknowledgments

We greatly appreciate the valuable contributions of Miriam Bipembi, Mark Cleur and Micheal Amponsah.

Authors contributions

Dr. Stephen Afenyo Dehlor and Christabel Sakpata Ewedji were responsible for reading, revising and approval of the final manuscript. Christabel Sakpata Ewedji was responsible for the research methodology, data collection and data analysis while Dr. Stephen Afenyo Dehlor reviewed relevant literature and wrote the introduction. Christabel Sakpata Ewedji drafted the manuscript and Dr. Stephen Afenyo Dehlor revised it.

Funding

Not applicable

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Canadian Center of Science and Education.

The journal’s policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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